TABLE OF CONTENTS

Abstract

Investigations into energy access in Sub-Saharan Africa often focus on modern energy transitions and electrification projects. However, these studies fail to consider the household level differences in access to energy sources and lack of opportunity to transition to alternative modern fuels. This study uses household-level data to explore household level reforestation efforts as a strategy to improve access to energy sources and improve environmental resilience on a community level. Specifically: Are reforestation efforts in Southern Malawi clustered in space, and do the surrounding land use land cover change classifications or household characteristics influence these efforts? The study, are conducted in southern Malawi with ultra-poor households that receive social cash transfer payments. Therefore, the focus of this study is on the most vulnerable, lowest income households in the community. It is expected that households with limited surrounding forest cover, and those who have received information on agroforestry or sustainable practices would be most likely to participate in reforestation efforts in the form of tree planting. There is observable spatial clustering of village clusters that have been provided information on agroforestry or sustainable practices and household-level tree planting efforts in village clusters, but the two are not found to be spatially correlated. We find that the total land owned by individual households is strongly correlated with tree planting efforts, especially in areas where wood is not primarily collected from plantations. Contrary to the expected result, reforestation efforts are not found to be linked to a current lack of access to energy sources, but are linked to land ownership. This study concludes that participation in un-aided reforestation efforts in southern Malawi may not be a mechanism for households to reduce vulnerability, but are a result of household characteristics like land ownership that enable the

ability to plant trees. This paper suggests that promotion efforts should consider other factors that are associated with the decision to reforest to be most effective in promoting sustainable practice.

Introduction

Biomass is the primary source of fuel for people living in rural areas in southern Malawi. This creates a strong link between the livelihood of rural people in Malawi and the availability of biomass suitable for household energy within the surrounding environment. As the population of Malawi grows rapidly, this dependence has increased (World Bank, 2018). At the same time, Malawi has experienced increasingly severe droughts as the globe continues to warm, and this has led to decreased crop productivity and associated food shortages (USAID, 2016).

Furthermore, the Southern region of Malawi is being deforested at accelerating rates, with agricultural production, charcoal production, and fuel consumption as drivers of deforestation and forest degradation (Jagger et al, 2016; Ngwira, et al. 2019). As the population depends more on a depleting supply of biomass fuel, efforts to reforest Malawi and the communities that are impacted most are increasingly necessary. Unfortunately, many reforestation efforts prove futile in impact, and a greater understanding of the mechanisms that drive reforestation efforts will be important for policy makers moving forward (Mauambeta, 2010).

What is the influence of energy access (as determined by location, distance and household characteristics) on fuelwood use and forest management efforts in 16 village clusters of Southern Malawi? The spatial component of energy access to fuel resources will be the focus of this study. Previous studies have explored the intersection between market participation and resource extraction in an attempt to understand the spatial patterns of forest degradation (Miteva, Et al. 2017). These studies focus on proximity and spatial characteristics to evaluate community level differences in in access to markets. This study will apply a similar methodology in terms of access to forest resources and the impact on

This paper contributes to this understanding from the alternative view of how resource extraction and reforestation efforts are impacted by geographic context. The geographic context is evaluated in terms of the time and distance to a fuelwood source (from survey data), and the land cover land use classification (from satellite data). As Malawi faces extreme population growth and decreasing access to energy as a result of deforestation, studies like this will help policy makers implement effective intervention strategies (Jagger & Kittner, 2017).

Background

Energy Access in Sub-Saharan Africa

Access to reliable energy sources has become a focus of international development agencies as energy poverty is often linked with health and income challenges. The potential for economic growth that comes with increased access to energy has made this issue a fundamental link in meeting the Millennium Development Goals (Srivastava et al, 2012; Brew-Hammond, 2010; Gujba et al, 2012; Sokona et al, 2012). Sub-Saharan Africa has one of the lowest electrification rates in the world with only 42% of the population having access to electricity in 2016, (World Bank Group, 2018) and 80% of the population relying on traditional biomass fuels for cooking.

Research shows that this use of biomass for meeting daily energy needs contributes significantly to the prevalence of health threatening household air pollution (WHO, 2014). Furthermore, Sub-Saharan Africa is largely considered one of the most vulnerable regions to global climate change due to the low resilience of rural communities as droughts and floods increase in severity and frequency. A low-carbon energy transition is strongly encouraged for the vulnerable region as the world moves towards renewable sources (Meckonnen et al, 2012). Due to the clear benefits of modern and renewable energy use, the majority of studies on energy access focus on the transition from "traditional" fuel sources (biomass, dung, crop residues) to "modern" fuels (LPG, biogas, electricity).

The energy transition is often viewed in terms of an energy ladder, with traditional fuel sources at the bottom of the ladder and renewable energy and electricity at the top of the ladder (Agbemabiese, 2012). However, transition to modern fuels is often more complicated than the ladder model might suggest, as many households combine different fuel types to meet energy needs (Brew-Hammond, 2010; Jagger et al, 2016). While it would be ideal to skip over the lower rungs of the ladder to the most sustainable and reliable forms of energy, there are critical challenges preventing rapid electrification in the region. These challenges include gaps in financial resources and unreliable electricity flow due to low generation capacities (Balachandra, 2011). Furthermore, the current generation capacity of many nations is reliant on renewable sources, like hydropower, that vary widely depending on the season. Hydropower generation capacity is also threatened by increased unpredictability due to climate change (Gujba, 2012).

The need for energy policies to incorporate several energy resource and technology options is of great importance to increase access (Brew-Hammond, 2010; Balachandra, 2011). According to Brew-Hammond in *Energy Policy*, "In the biomass area, developing sustainable supplies at community level is an attractive option, as it yields positive results both at the level of environmental protection and income generation," (Brew-Hammond, 2010). This study hopes to explore community wide reforestation efforts as a method of improving energy access and boosting the capacity of a community to adapt or mitigate the effects of climate change.

Vulnerability and the Causes of Deforestation

Vulnerability and adaptability are guiding themes in the literature on resource utilization and reforestation efforts in Sub-Saharan Africa and developing nations across the globe. The question of vulnerability is especially relevant to this study because "…while global warming is changing the world, the distributional effects and risks associated with those changes follow the contours of social power and inequality," (Faye & Ribot 2017). The high levels of poverty and the resulting low adaptive capacity of the population in southern Malawi and much of Sub-Saharan Africa makes this region particularly vulnerable to climate effects.

The ability of a population to adapt to changes in the environment is increasingly important, but this ability requires a level of planning for the future that is currently not feasible in Malawi where people occasionally have to sacrifice sustainable and long-term livelihood to fulfill short-term needs (Hartter & Boston, 2007). This desire to "consume in a world of scarce resources" is outlined in a classic piece of literature called "The Fuelwood Crisis and the Environment" that started conversations about the "fuelwood crisis in Africa" (Pearson & Stevens, 1989). While the distinction of environmental 'crisis' was premature, the theme of deforestation as a result of the growing global energy demand and the lack of sustainable land use has sparked a focus on resource consumption, sustainability, and adaptation.

There is not a consensus on the mechanism that causes deforestation in areas of the world that depend highly on wood resources for meeting energy needs. Some papers insist that the extraction of wood resources for fuel is a leading cause of forest degradation (Bailis et al 2015, Jagger & Perez-Heydrich 2016, Schulte-Bisping et al 1999) while some claim that the deforestation is caused by agricultural land conversion (Hyde & Seve 1993, Pullanikkatil et al 2016, Zulu 2010) and others approach the question as still unanswered (Webb & Dhakal, 2011).

The question of responsibility plays a role in the recommendations to policy makers to improve the environment and resulting resilience of nearby populations. For example, those who focus on the importance of fuelwood collection on deforestation rates propose the implementation of reforestation efforts, improved cookstove programs, or fuel substitution and diversification as short- and long-term techniques to improve the resiliency of communities (Jagger & Perez-Heydrich 2016). However, Pullanikkatil argues that the main driver of deforestation is the demand for agricultural land as the population grows (Pullanikkatil et al 2016). Accordingly, reforestation efforts would not prove effective in preventing deforestation if these reforestation efforts are done in a mini plantation or agroforestry style that would increase the demand for agricultural land and decrease the need for energy efficiency (Heltberg et al, 2000).

Similarly, Hyde and Seve warn that enabling smallholder community members to plant trees via reforestation initiatives could lead to a decrease in demand for market fuelwood, which would result in an increase in the price and corresponding value of this wood (Hyde & Seve 1993). The increased value of trees for fuelwood could exceed the value of agricultural land, which would result in households planting trees on the highest value land which is closer to the community and further from the forest. This reversal in prioritization could force agricultural lands into the fringe of the indigenous forest. Hyde and Seve conclude that “shifts in the general location of trees and forests may alter the locus of watershed management problems,” and lead to greater erosion as the tree cover is removed where the forest once stood (Hyde & Seve 1993).

The cause of high deforestation rates requires more investigation to provide well informed recommendations to policy makers on how to best implement sustainability programs in the future. It is possible that reforestation efforts will require proper management to see environmental benefits. The survey data from Southern Malawi provides insight into this debate with data on the amount of fuelwood stored for energy usage and the land type from which fuelwood is retrieved. It is worth noting that 96.6% of interviewed households used collected wood as an energy source for cooking and heating water within a year of the interview, while only 10% used purchased fuelwood in the same timeline. Due to the widely referenced preference for free resources when available, the market demand for fuelwood is assumed have minimal impact on the studied communities. However, purchased fuelwood may be explored as a potential response to lack of available nearby fuel wood.

The survey results found that 84% of respondents who collect fuelwood reported that their method of collection was to gather deadwood from the forest; a practice that would not contribute to high deforestation rates. These results are supported by numerous studies that the majority of fuelwood collectors prefer dead and dry wood over live trees, because the dead wood is both lighter to carry and easier to keep aflame (Preston et al 2017, Zulu 2010). The fact that dead, dry wood is lighter to carry is important considering 96% of respondents to the 2017 household survey reported carrying fuelwood back to their households by headload. While this suggests that deforestation is not caused directly from fuelwood collection, reforestation efforts may still be a solution to the uncontrolled environmental degradation.

Efforts to Prevent or Reverse Deforestation

Forest coverage in Malawi has decreased from 34.4% in 2010 to 33.3% in 2015, a 1% decline in total forest coverage (World Bank, 2018). Furthermore, the Miombo woodlands of which Malawi is apart deforest at between 0.2 – 1.7 % per year (IPCC 2014). A popular suggestion for counteracting this decline is to implement reforestation efforts in the area to provide households with a sustainable supply of fuelwood. However, most studies agree that the success of reforestation efforts at a large scale will require outside parties (be that the government or non-governmental agencies) to provide smallholders with the necessary seedlings (Hyde & Seve 1993).

However, all case studies do not find this recommendation to be necessary, as in the Chemoga watershed in Ethiopia which has experienced an increase in forest cover over the past few years without the help of an outside party. This unaided reforestation effort was attributed to replanting efforts in an attempt to make up for overall wood scarcity in the area (Bewket 2003). Inspired from these findings, this study will explore the potential for unaided reforestation efforts to improve access to energy sources as a result of general fuelwood scarcity.

Access to forest resources is influenced strongly by the availability of plantations or agroforestry. Village woodlots or plantations are found to decrease the probability of fuel wood collection from natural forest, but this trend is not valid if the village woodlot is close to the forest area (Kohlin & Parks 2001). This may be in part due to the villagers view of the woodlot as a collective managerial action more than a technique in preserving the forest, and the proximity of the two sources will not lead to behavioral changes from the community (Kohlin & Parks 2001).

Planting trees and participating in reforestation efforts requires a certain level of land ownership, and can create inequalities in fuelwood access between those who own land and those who do not. Webb & Dhakal explore this correlation between land ownership and vulnerability by evaluating tree planting behavior on agricultural land in Nepal. The conclusion of the study is that the household characteristics do not influence the participation in planting efforts on agricultural land if the local forests have an abundant supply of wood because of the decreased need for private supply when the public supply is plentiful (Webb & Dhakal 2011). Therefore, the supply of public fuel wood has been found to influence the behavior of local community members.

Numerous papers explore the correlation between reductions in fuelwood accessibility and the substitution of lower quality fuels (Brouwer et al 1996, Heltberg et al 2000, Jagger & Perez-Heydrich 2016, Preston et al 2017, Zulu 2010). The fuel ladder moves from dung and crop residues to fuelwood to charcoal the so called "modern" fuels of LPG and electricity (Preston et al 2007, Zulu 2010). The inferior fuel types of dung and crop residues are often substituted for fuel wood in times of scarcity, but they come with disadvantages like the time and care spent when cooking with these low-calorie content fuels (Brouwer et al, 1996). While the mixing in of inferior fuel types during times of scarcity is well recorded, a potential policy misconception is that the modern fuel types like LPG and electricity will replace the biomass fuel types as a solution to deforestation and environmental degradation in the future.

In practice the "modern" energy transition is not yet economically feasible for the majority of households in Southern Malawi or rural Sub-Saharan Africa (Preston et al 2017). Accordingly, Zulu argues that the running policy of the Department of Energy Affairs to wait for energy transitions from biomass to modern fuels on the energy ladder is "…a misguided and disjointed energy policy," (Zulu 2010). Furthermore, Zulu goes on to describe the expectation of the Malawian government to decrease the use of charcoal (for its significant environmental impact) by implementing a charcoal ban as both "unrealistic and untenable" (Zulu 2010). This is due to the strong preference of communities to mix fuel types and substitute out scarce resources.

Finally, on the national level, the traditional way to protect natural resources is via state-ownership and the establishment of nationally protected areas. However, during the field work for the 2017 survey, multiple trips were taken to national forests or preserved areas and Malawians were observed collecting fuelwood in the open, undisturbed by the presence of researchers. According to a study by Abbot and Mace in 1999 in a protected area of Lake Malawi, the law enforcement of the protected area had little effect on the collection of fuel wood from within the park boundaries (Abbot & Mace 1999). They concluded that this was due to both the lack of consistent patrolling, and the sheer size of the protected area. The number of days per month that the area is patrolled is approximately 6.6, with an average encounter with local fuelwood collectors at 1 per patrol (Abbot & Mace 1999). Furthermore, the punishments for being caught collecting fuelwood in the protected area was relatively small and ineffective.

The leniency in the law enforcement may be attributed to the dependency of rural communities on this forest, and the increasing focus on charcoal as a major cause of deforestation unlike small scale fuelwood collection (Abbot & Mace 1999). The majority of fuelwood collectors prefer dry, dead wood that is lighter to carry and easier to light. On the contrary, charcoal producers prefer using live trees because the moisture in the wood is vital for the charcoal production process, which results in deforestation rates 4 – 12 times higher than that of fuelwood directly (Preston et al 2017).

Spatial Patterns of Access

Fuel usage and fuel wood collection behavior has been modeled as a function of spatial proximity (He et al 2009, Jagger & Perez-Heydrich 2016, Kohlin & Parks 2001). Specifically, the spatial patterns of fuelwood collection have been evaluated to model environmental interactions and enable the design of effective conservation strategies (He et al 2009), and efficient intervention methodology, like the implementation of village woodlots to reduce forest degradation at various distances from the community (Kohlin & Parks 2001). Distance is often used as a measure of the accessibility of fuel resources, but some literature has explored household level factors that influence the ability of a household to access resources, and found that labor constraints and wealth play larger roles in determining access than distance. (Brouwer et al 1997). This finding will be considered when determining the household level access to fuelwood in the overall study.

The proximity of a household to a given market has been found to directly influence the likelihood that the household participates in selling fuel wood or charcoal (Miteva et al 2017). Daniela Miteva and her team at Ohio State University studied the spatial patterns of market participation and resource extraction in Northern Uganda and found significant correlation between proximity to the market or forest and the utilization of either. Specifically, the study found that households that did not participate in the market (collected their own resources) were often found at the furthest distances to the market and closest to the forest, while the households that relied solely on the market for resources were found closest to the market itself. Finally, the households that sold the biomass materials at the market were often found at intermediate distances with equal access to both (Miteva et al 2017). This study applies a similar spatial pattern model to find correlations between reforestation efforts and access to nearby forests using the household survey locations and land use land cover change classifications.

The Study Area

Malawi Context

Malawi is a small country in southern Africa (see Figure 1) with a dense population of 18.6 million people in a little under 46,000 square miles (USAID, 2018). Malawi has one of the lowest gross domestic products per capita at $1,084 (in purchasing power parity), and is experiencing accelerating deforestation and resulting environmental degradation (Hansen et al, 2013). The study area is in a region of the world that only contributes a small portion to the worlds CO_2 emissions, but is at risk to be significantly affected by the resulting change in the global climate as droughts and floods negatively impact crop yields (Bandyopadhyay et al, 2011; Srivastava et al, 2012; Wellard et al, 2012). Furthermore, Malawi has an extremely low rate of electrification at 1% in the rural areas (study areas) 46% in the urban regions, and 10.8% access rate determined by overall connections (USAID, 2018). Furthermore, the generation capacity of Malawi consists of nearly 88% hydroelectric power that varies seasonally as droughts bring the lake levels down.

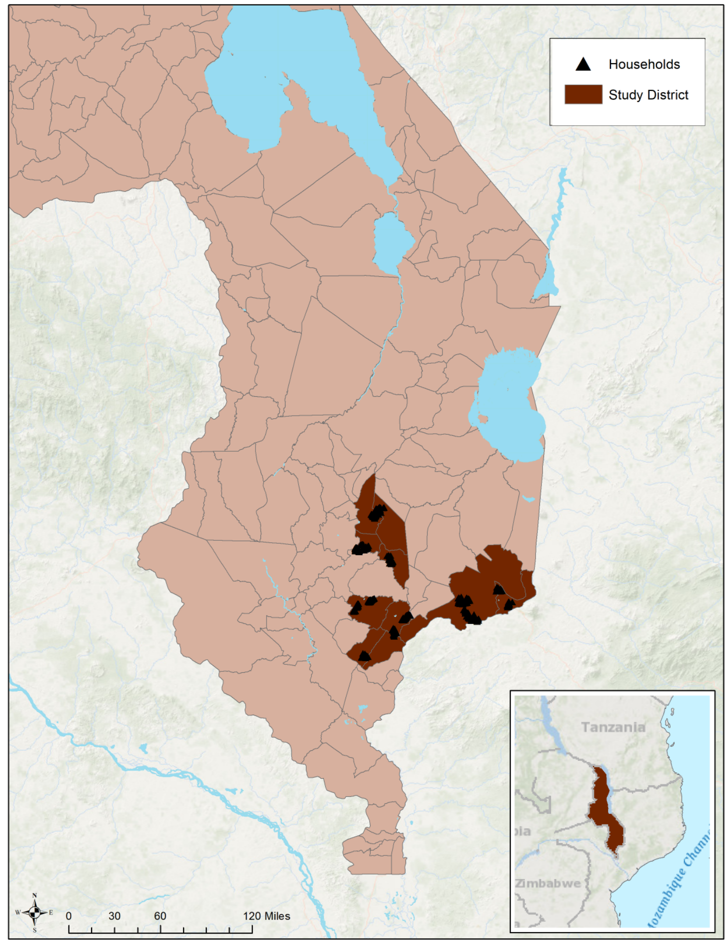
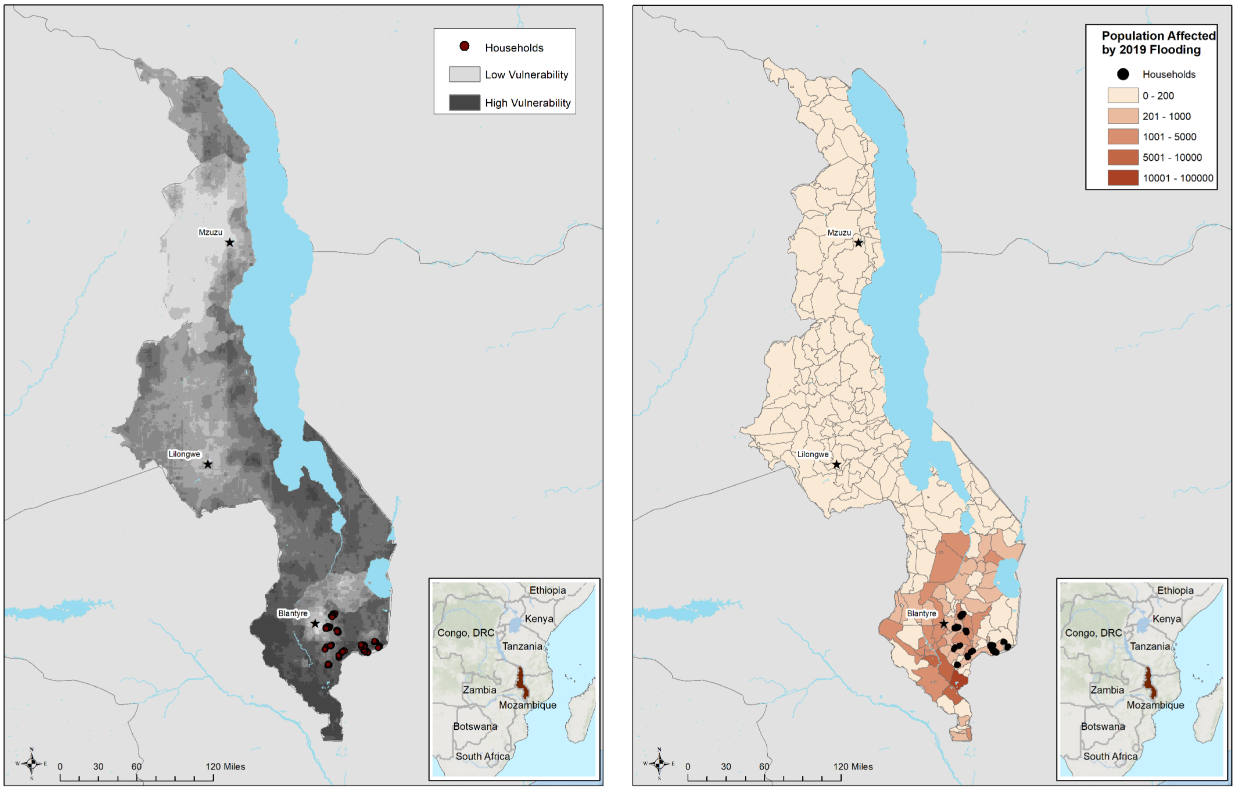


Figure 1. Map of Study Districts in Southern Malawi
The study districts are highlighted in dark red, and the individual households are marked with black triangles. Malawi is a landlocked nation in sub-Saharan Africa as indicated in the inset map of Malawi's location on the continent.

Southern Malawi and Tropical Cyclone Idai

Three districts in Southern Malawi were chosen to conduct the interviews for this project. Southern Malawi experiences higher deforestation rates than the Northern part of the country (Jagger & Perez-Heydrich, 2016), and is at higher risk to adverse climate effects (see Figure 2A). Climate change threatens to cause stronger and more frequent extreme weather events in the future. This study will explore reforestation efforts as a form of increasing energy access while decreasing the environmental degradation and vulnerability caused by high deforestation rates.

While writing this paper in March 2019, a deadly cyclone hit the eastern coast of Africa left behind catastrophic damage in the southern areas of the country. Cyclone Idai was one of the worst tropical cyclones to hit Africa and was the third deadliest tropical cylone on record. Reports warn that this storm might be indicative of the increase in dangerous weather events due to climate forcing (John, 2019). Such storms post a dangerous threat to the vulnerable and impoverished rural populations in Southern Malawi and Mozambique (see Figure 2B). The risk of increased climate variability, low rates of electrification, and high deforestation rates make Southern Malawi a unique and crucial location of study.



Figures 2A. B. Climate Vulnerability of Southern Malawi
These maps were generated using data from (a) The Regional Centre for Mapping of Development Resources (RCMRD) developed with Malawi Department of Disaster Management Affairs (DoMDA) developed for SERVIR a USAID-NASA project and (b) Netherlands Red Cross. The vulnerability index is a determined by combining measures of exposure, sensitivity, and adaptive capacity for Malawi. The flood data is a measure of affected people per district developed from Sentinel satellite imagery (from March 7^{th} to March 14^{th}) and high-resolution settlement layer grids.

Methodology

Data Collection

This project collected data in the summer of 2017 using a survey which was the first of a three-year study funded by the National Science Foundation (NSF) to examine the changes in Southern Africa's coupled human, terrestrial and atmospheric systems. The survey was conducted in three distinct districts in Southern Malawi: Mulanje, Thyolo, and Chiradzulu. The data collection required two months of field work with a team of 10 Chichewa speaking locals to complete a total of 900 household surveys. The households were chosen based on their distinction as a social cash transfer program (SCTP) recipient. The SCTP targets ultra-poor and labor constrained households to provide a cash payment in an attempt to improve livelihoods and reduce inequality (Garcia & Moore, 2012).

The survey collects data on the poorest and most vulnerable households of each community. The districts chosen for this survey were picked as 2 treatment and 1 control regions, as the SCTP program is present in only 2 of the districts, and improved cookstoves (Chitetezo Mbaula) have been provided to those treatment districts as well. The survey will be evaluating the adoption rates of these improved cookstoves, but this part of the survey will not be used for this study. The survey takes between 1-3 hours per household and asks various questions about the daily lives and fuel use of respondents (see Table 1 in appendix for module descriptions).

Data Analysis

The variables of interest are isolated from the main dataset, and the households are summarized into the 16 interviewed village clusters. The mean center of all the data points in each village cluster is used as an approximation for the middle of the village cluster. This is necessary, because there is no precise geographic boundary for the village cluster administration level. A 3 km buffer is created to measure the forest cover and deforestation rates of the area surrounding the village cluster. This buffer distance is chosen because greater than 70% of respondents reported a fuelwood collection distance within or equal to 3 km, and every interviewed household is located within a 3 km buffer of the mean center of the respective village cluster. Theisen polygons were not used in this study, because they would misrepresent the space that the interview results represent. Malawi has a high population density, and the variation in unrepresented village clusters will not be summarized into interviewed clusters with Theisen polygons. The deforestation rates are determined by the change in percentage of forest classified land from the Sentinel satellite within each buffer from 2000 to 2013. The percent forested is determined from the percentage of forest classified land in 2013 alone. The land classified as forest was ensured to not include the bright green tea plantations that are common in the Mulanje and Thyolo regions by visual comparison to the provided dataset.

The household level data is then summarized into each village cluster using the averages of the variables of interest (see table 6 in appendix). The yes/no questions are then indicative of the percentage of yes' (value of 1) compared to the percentages of no's (value of 0). New fields are created to indicate the household's response on where they most frequently collect fuelwood (type and ownership of the land). These new fields are able to take a categorical variable and create a yes or no binary that indicated which descriptor was the primary type or ownership of the land fuelwood is collected from. Each of these values of interest are placed into a correlation matrix using excels correlation data analysis add in to see general trends in the data (see Table 4 in appendix). Time and distance (in km) are collected for each question regarding proximity, but only the time variable will be used in this study for simplicity. These variables have been cleaned for extraneous values and have a strong correlation (> 0.99 in the correlation matrix). Finally, the difference between the future expected wealth step and the current perceived wealth step was calculated as an indicator of positive outlook for the future.

A variance inflation factor of the variables of interest is calculated to reduce multicollinearity of the dataset (see Table 3 in appendix). The new binary fields generated from the categorical questions had a high co-dependence as each household may only indicate yes on one of the descriptors. Therefore, the study only runs regressions on one of each of these categorical variables at a time. The linear regressions were conducted in R using an ordinary least squares linear regression model, and the classic spatial regressions were conducted using GeoDa software. Spatial clustering analyses are conducted using uniform Kernal weights. A global clustering analysis in SatScan was used to highlight the nearby village clusters that had high and low percentages of reforestation efforts (see Figure 4B). The global clustering was modelled using a Poisson distribution without a buffer limit. Finally, Moran's I values from the kernel weighted clustering analyses in GeoDa are used to measure general clustering behavior of the variables (see Figure 1 in appendix for description of weights). This clustering is used to guide the regression variables.

Results

The land use land cover change classifications are broken down into three categories. These categories describe areas with varying rates of deforestation and current forest cover. The classifications are not found to be clustered in space, but are used as descriptors to distinguish between various environmental surroundings (see Figure 3).

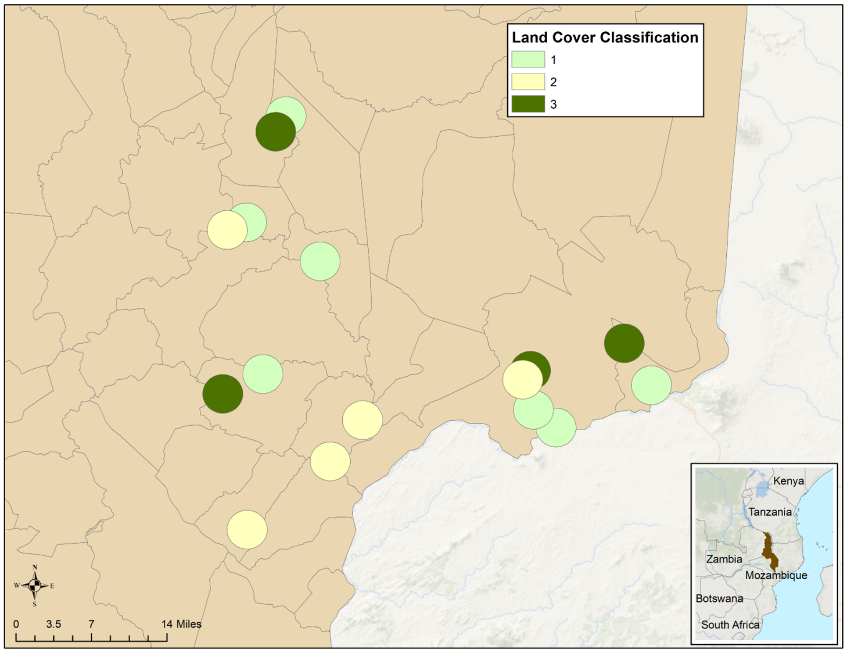


Figure 3. Land Use Land Cover Change Classifications Map
This map indicates the land use land cover change classification (1-3) determined from the deforestation and forest cover percent for 3-kilometer buffers from each village cluster center. Category 1 is defined as low forest cover (< 7%) and low deforestation (< 22%), while category 2 has high deforestation (>22%) and low forest cover (< 7%). Finally, category 3 represents high forest cover (> 7%) and low deforestation (< 22%).

Reforestation efforts in this paper are measured primarily using self-reported data on tree planting. The survey also collected data on post-harvest management and measures to encourage re-growth, but the response rates for this variable were low at 8.3% compared to 26.2% that reported planting trees in the past 5 years. Furthermore, the post-harvest efforts were distributed randomly in space with no observed spatial correlation (Moran's I: 0.0709). This is why tree planting efforts are the focus of this paper, as the primary form of sustainable reforesting efforts. A local clustering analysis was run on tree planting observations at the village cluster level using Kernal weights (see Figure 1 in appendix). The local clustering of tree planting behavior is indicated with the moderate 0.3601 Moran's I. A global clustering analysis was also run on the household level tree planting (see Figure 4B) in SatScan, and there are multiple clusters of high and low tree planting reports on the household level.

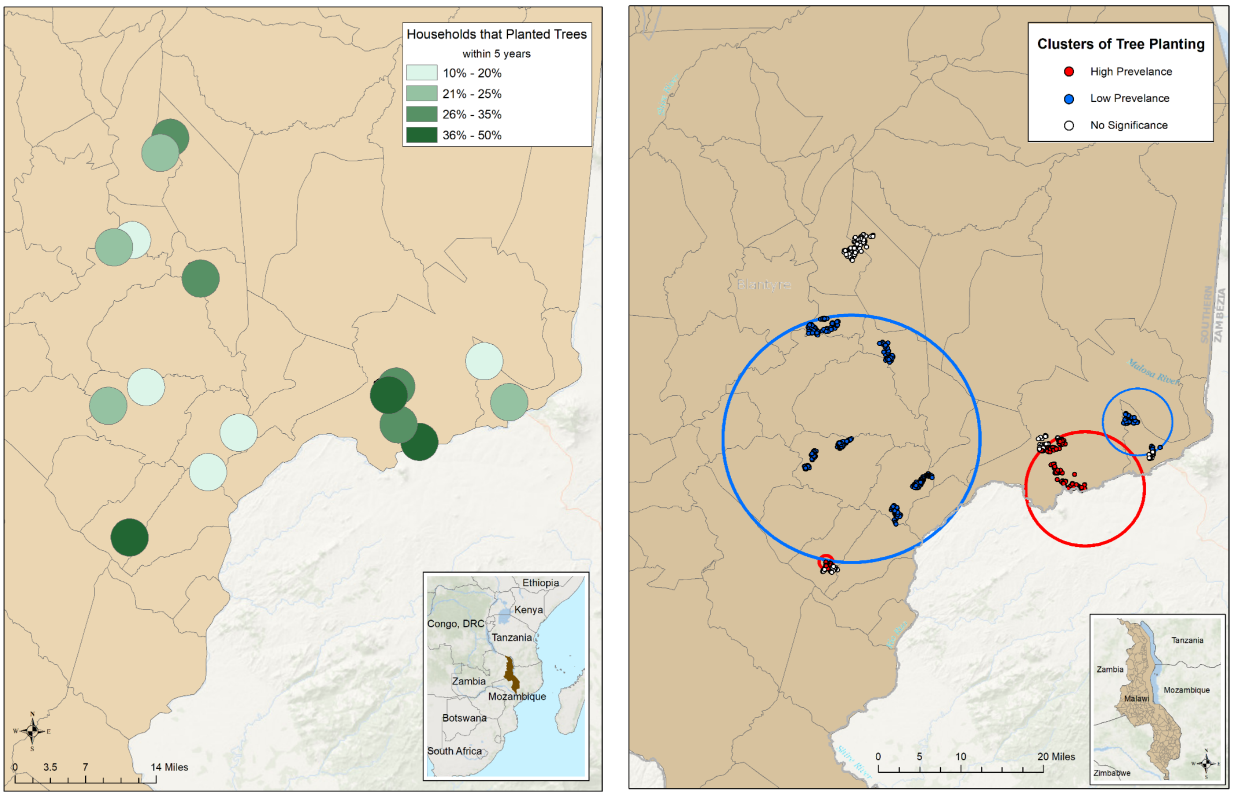


Figure 4A. B. Reforestation Efforts as a Percentage of Total Households in each Village Cluster and B. Clustering of Reforestation Efforts at the Household Level

The main focus of the data analysis was on the impacts of various land cover types and energy access indicators on the participation of a household in reforestation efforts as measured by tree planting within 5 years of the interview. These figures show the raw values (a) and clustering analysis (b) of tree planting at the village cluster level for the 16 village clusters interviewed in southern Malawi. The clusters were generating using a Poisson model in SatScan clustering software.

Moran's I values are used as an indication of clustering over local space. A Moran's I value of 1 would represent perfect clustering, and -1 would represent perfect dispersion. The local clustering of several variables is indicated in Table 2. The significance of this clustering value is indicated with the pseudo p-value as determined with 999 permutations over space (Table 2).

Variable	Morans I	Pseudo P-Value (999 Permutations)
Total Land Owned	0.697 **	0.002
Information on Agroforestry	0.629 **	0.008
Land Use Land Cover Change Classification	0.138	0.35
Planted Trees	0.360 *	0.09
Distance to Home Forest	0.293	0.18
Wood Hard to Get (perception)	0.237	0.33
Time to Collect Fuelwood	0.270	0.23
Post-Harvest Efforts	0.0709	0.12
Collect Fuelwood from Forests	0.477 **	0.04
Collect Fuelwood from Plantations	0.574 **	0.01
Collect Fuelwood from Own Farm	0.458 **	0.04
Collect Fuelwood from Not Owned Farm	0.215	0.39
Collect Fuelwood from Government Owned Land	0.497 **	0.02
Collect Fuelwood from Community Owned Land	0.518 **	0.005
Collect Fuelwood from Privately Owned Land	0.596 **	0.009
Collect Fuelwood from Open Access Land	-0.0020	0.02

Table 2. Spatial Clustering results using Morans I value of Local Clustering
The spatial clustering of several village cluster level variables is conducted and a Moran's I result suggests the strength of this spatial clustering. These are calculated using uniform Kernal Weights in Geoda. Two stars indicate a significant trend of local clustering. One star indicates a variable of interest with an observable trend that is not statistically significant over 999 permutations.

The Moran's I values can be represented through a clustering map as shown in Figures 5 and 6. Figure 5 represents the local clustering of 3 variables with significant Moran's I correlation from Table 2. Figure 6 uses a bivariate local clustering analysis to show the correlation between two variables as a form of clustered space. These clusters are generated by calculating the average of the neighbors of the dependent variable and comparing this to the relative value of the independent variable (written in order of independent to dependent in the caption of Figure 6). Figure 6A compares total land owned and lagged trees planted (Moran's I 0.533 with a p-value of 0.008), and 6B compares fuelwood primarily collected from private land

and lagged fuelwood primarily collected from plantations or woodlots (Moran's I 0.553 with a p-value of 0.007).

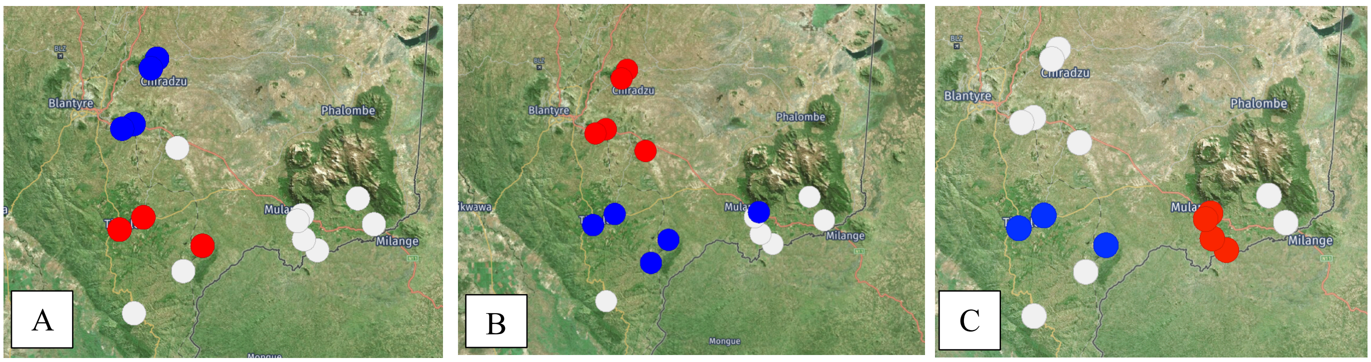


Figure 5. Univariate Clustering with Kernal Weights
(a) Households that primarily collect fuelwood from private land (b) Information received on agroforestry and (c) Total land owned. The dark red values show areas with High-High clustering (high value surrounded by high values), and the dark blue represent Low-Low clustering (low values surrounded by other low values).

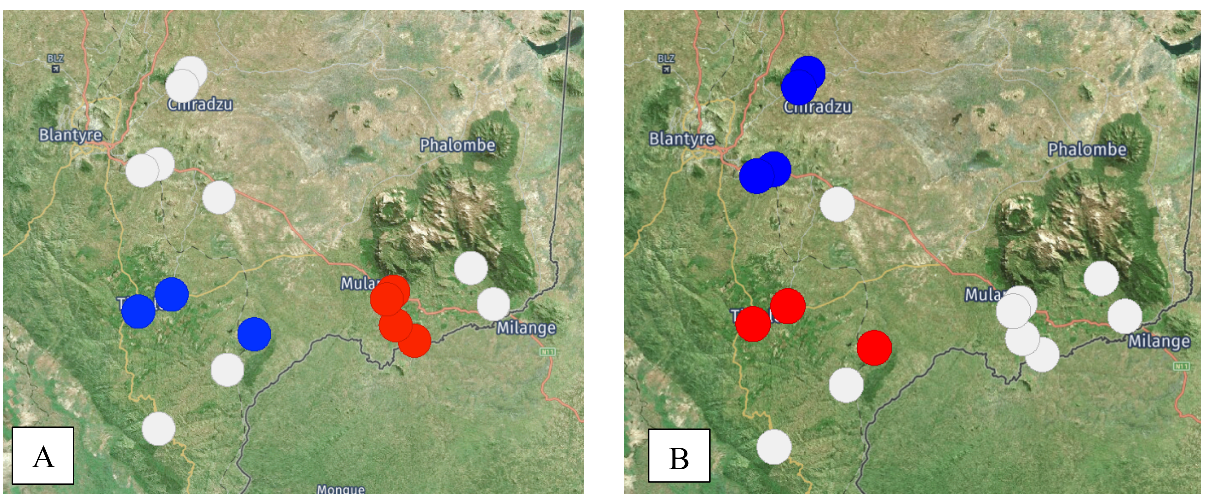


Figure 6. Bivariate clustering with Kernal Weights
(a) Total land owned by households lagged with households that planted trees (Moran's I 0.533 with a p-value of 0.008), and (b) Fuelwood collected from private land compared to Fuelwood Collected from Plantations (Moran's I 0.553 with a p-value of 0.007). The clustering shows dark red (High-High clustering), dark blue (Low-Low clustering), and light blue (Low-High clustering).

Discussion

This study used several techniques to explore the factors that influence reforestation efforts in Southern Malawi. The results indicate several variables are spatially clustered, and correlated over space. However, the differences in household characteristics over different land cover land use change classifications is left unclear from the data. This will be explored further below. Furthermore, there is distinct clustering of the spread of information on agroforestry as reported by households. This trend does not correlate with the clusters of tree planting activity as would be expected. The factors that do spatially correlate with tree planting activity are explored in an attempt to understand the discrepancy between the expected impact of agroforestry promotion and the observed trends. Finally, fuelwood is largely reported as being difficult to collect with 85% of participants agreeing that fuelwood is difficult to obtain. There is one district that stands out with only 68% of the participating households reporting that fuelwood is difficult to obtain. This cluster will be further explored to see if this perception has an observable impact on reforestation efforts.

Clustering of Indicators of Access

Clustering of tree planting behavior is observed (see Figure 4B), but there are no observed clustering of post-harvest care efforts (Moran's I of 0.0709 in Table 2). This may be a result of the extremely low number of households that reported participating in post-harvest care (~10% of total households). The most significant variable related to reforestation efforts is found to be a positive relationship to total land owned for both the linear model at the household level, ($p < 0.01$) and the bivariate spatial clustering at village cluster level (Moran's I of 0.533 in

Figure 6A). Finally, the total land owned by a household is negatively correlated with the perception of wood being difficult to collect ($p < 0.02$). This might suggest that with more land owned, a household has more capacity to plant trees and collect from a nearby location. Tree planting activity requires land to plant on, and may not be a feasible option to improve energy access for all.

Finally, the location from which a given household collects wood is strongly correlated with the ownership of the land as shown by the bivariate clustering in Figure 6B. Village clusters that largely collect fuelwood from plantations are clustered in the same areas as households that largely collect fuelwood from private land (see Figure 6B). Village clusters that collect most often from the forest is strongly negatively spatially correlated with collection from privately owned land (Moran's I of -0.503 and P-Value of 0.02). Reforestation efforts are not found to significantly correlate with any type of land from which fuelwood is collected. It is a surprise that tree planting is not associated with households collecting fuelwood from their own farm or negatively correlated with collection from forests.

The reason a household planted trees was asked if a household responded yes to planting trees in the past 5 years (see Figure 2. in appendix). These responses show that fruit was the primary overall reason cited for planting trees (34.7 %), with fuel following with 31.1 % of the total reasons. However, 55.9 % of respondents cited fruit as the first reason for planting the trees and only 25.4 % cited fuel first. This suggests that tree planting is not primarily used to increase access to fuel wood. A question is asked on the survey about total planted forest, but this question refers to the acres of woodlot owned by the household not efforts to reforest (see table 2 of appendix).

Differences in Land Use Land Cover Change Classifications

Land cover land use change classifications are predicted to have distinct differences in means for characteristic variables like distance to home forest (5 minute difference) or perception of future improvement (12.5 % difference). However, the categories are a simplified model of the land types, and are not found to be significantly clustered in space on a village cluster level (Table 2). Therefore, the impact of land classifications on household level characteristics will be primarily be evaluated using ordinary least square regressions and t-tests of the household response data. For example, the perceived future improvement variable was highest for land classification 1 (low deforestation and low forest cover) and lowest for land classification 3 (low deforestation and high forest cover). A T test was run on these two household level responses and the difference in means was determined to be close to statistically significant ($p \sim 0.06$). This was unexpected as high forest cover was hypothesized to be an indicator for future resilience and energy access. However, this result is merely descriptive in nature, because this trend might be impacted by how low or high the current wealth status of individual households is evaluated. The current wealth perception is in fact highest for land cover 3 (1.24) and lowest for land cover 1 (1.18). The difference in means of the current wealth perception is not statistically significant ($p \sim 0.14$).

The difference in future improvement might be due to a better perception of current standing in the community in the high forest cover environment. Furthermore, a difference in means was determined for the change in time spent collecting fuelwood over the past 5 years. Land cover classification 3 had the perception of the most change, and category 1 had the perception of the least change ($p \sim 0.07$). The observable differences in perception of fuelwood access and wealth was greatest between high and low forest cover, while the mean for the high deforestation land cover classification remained between the other two. This should be further explored, but it is possible that changes in high forest cover areas are noticed more readily than large changes in areas with low forest cover. Whether these differences may be explained by responses to scarcity will be explored further below.

Influence of Agroforestry Promotion

There is a significant positive linear relationship between reforestation efforts in the form of planting trees and receiving information on agroforestry at the household level ($p < 0.05$). However, at the village cluster level, the spatial regression shows an inverse relationship between reforestation efforts by planting trees and receiving information on agroforestry (see Figure 5B). This suggests that while households were more likely to respond that they had planted trees in the past four years if they had received information about agroforestry and sustainable forest practices, this trend does not remain present at a village cluster scale. This may be due to the way agroforestry information is parsed out, which is in a very clustered and spatially specific manner. Furthermore, the tree planting behavior on a village cluster basis was spatially concentrated independent of the agroforestry information. This might suggest that the information is not the reason communities are participating in reforestation efforts, as these efforts are clustered in different zones in space.

Case Study of Nakholu

The variable for perception of wood collection difficulty (wood hard to get) is quite high across all households with an average of 85% responding yes. However, there is one village cluster, Nakholu, that reports a difficult time collecting wood in only 68% of households. Other factors were explored in a case study of this village cluster to see the characteristics that might have contributed to this large difference in perception.

The number of households that responded that they planted trees in the last 5 years was twice as high as the total average (50% vs. 26.2% respectively). Total land ownership is also slightly higher in terms of average acreage at 1.57 acres vs. 1.21 for the entire study. 84% of these households collect fuelwood from private land, with 44% coming from plantations and 32% from forests. This village cluster may be indicative that with tree planting efforts, there is a lower perception of difficulty to obtain fuelwood and potentially greater access to energy resources. Conclusions will not be drawn based on a single village cluster, but Nakholu provides insight into the cluster level differences that might be influenced by the household level characteristics discussed in this paper.

Conclusions

This study has explored reforestation efforts in southern Malawi as a form of improving energy access and reducing vulnerability to climate change in rural communities. The analysis used survey results from the summer of 2017 from social class transfer households in 16 village clusters. Furthermore, the land use land cover change of the village clusters was used to classify the clusters into 3 types of land cover land cover change categories. This classification was used to describe differences in the way communities interacted with their environment, and it was hypothesized that less access to forest resources due to deforestation rates would promote reforestation efforts in the form of tree planting activity. No significant trend was found in the differences between land cover categories, but there were other household level characteristics that appeared to influence the participation in reforestation efforts. The strongest correlation was a result of total land owned, especially when looking at households that collected from private land. Furthermore, it was expected that information on agroforestry might influence households to plant trees, but this trend was not observed in the study districts. In fact, the areas which had more households report being given information on agroforestry reported lower levels of tree planting. This may be a result of the type of land from which fuelwood is collected in these areas, primarily from forests. This study concludes that more research needs to be done into the factors that influence reforestation efforts to create more effective reforestation initiatives. As discussed in this paper, reforestation is a unique way to increase access to energy sources and decrease the vulnerability of already sensitive regions.

The biggest limitation of this study is the determination of “reforestation efforts” as defined by households that participate in tree planting. However, responses indicate that fuel is not the primary reason that households plant trees, and fruit is a greater priority. Efforts to reforest or practice sustainable fuelwood collection may be indicated by post-harvest care, but this variable received low response rates overall for the interviewed districts. It is suggested that reforestation efforts may be a result of ability and not necessity, in which case the most vulnerable and labor constrained households in each community (SCTP households) is not the best sample for determining why households participate in reforestation efforts. This study could therefore be improved with a random selection of households, and more detailed questions about the meaning reforestation.

This study hopes to continue work on reforestation efforts and energy access by developing an indicator for energy access that includes access to forest resources. Especially because areas with easy access to free forest resources are less likely to undergo a modern energy transition without economic motivation. I hope to include land ownership, energy alternatives, perception of access, physical distance, LULCC, and household level demographics in the energy access model. Furthermore, GPS tracks have been taken in this study area, and these will be used as a measure of access and distance to forest resources (including but not limited to fuelwood). These tracks will be used to validate current assumptions on distance to forests, and popularity of collecting lower quality fuels or crop residues instead of wood fuel. Finally, this study hopes to expand on the exploration of the effects of providing information on agroforestry and sustainable practices with case studies of actual reforestation information efforts to enable better distinction of the treatment and control areas.

Appendix

Module	Name	Module	Name
A	Household Identification	M	Household Fuel Consumption Cooking and Heating Water
B	Household Roster	N	Short Recall Use of Fuels for Cooking
C	Household Characteristics and Facilities	O	Household Fuel Consumption for Lighting
D	Household Assets	P	Household Fuel Consumption for Space Heating
E	Land and Livestock Ownership	Q	Household Fuelwood Collection
Ea	Forest Resource Management	R	Biomass Related Business Enterprise
F	Social Capital and Trust/community cohesion	S	Income from Agriculture and Livestock Production
G	Shocks and Vulnerability	T	Income from Forests and Other Wild Areas
H	Time Use	U	Other Sources of Livelihood/Income
I	Health Impacts	V	Household Energy Expenditures
J	Knowledge and Perceptions about Stoves and Cooking	W	Household Cash Expenditures and Purchases in the Past 12 months
K	Household Cooking and Water Heating	Y	Fuelwood weighing
L	Short Recall Use of Stoves		

Table 1. Household Survey Questionnaire Modules

The survey consists of 25 sections with many questions in each section. There are 2547 resImagine a stairway with 6 steps – on the bottom step (step 1), we have the poorest people in the community; on the highest step we have the
ponses over a wide array of question types. The above chart gives a better understanding of the types of questions asked in the survey and the information that is collected.

Description	Question	Answer Choices / type
Total Land Owned	Total land owned (including land rented out)? [Sum of Agricultural Land, Owned Natural Forest, and Owned Plantation Land]	Acres
Planted Forest	Total planted forest/woodlot owned (acres)	Acres
Current and Future Wealth Step	Imagine a stairway with 6 steps – on the bottom step (step 1), we have the poorest people in the community; on the highest step we have the richest people. On which step would you say you are on now?	1=Poorest, 2=Almost poorest, 3=Middle, closer to poor, 4=Middle, closer to rich, 5=Almost richest, 6=Richest
Information on Agroforestry	Has any member of the household received information	No=0: Yes=1

	on agroforestry or tree planting in the last 12 months?	
Planted Trees	In the past 5 years has your household planted trees?	No=0: Yes=1
Reason trees were planted	If yes, what were your reasons for planting trees?	1=Fruit, 2=Fodder, 3=Fuel, 4=Ornamental, 5=Biofuels (i.e. ethanol), 6=Fencing/construction, 99=Other, specify
Distance to Home Forest	How far is it from your household to the edge of the nearest natural forest/woodland that you have access to and can use? (In distance)	Kilometers
Wood Hard to Get (perception)	Read the following statement and ask respondent whether he or she agrees (yes), disagrees (no) or has no opinion. (Firewood is hard to obtain)	No=0, Yes=1, No Opinion=2 (No opinion eliminated from analysis)
Time to Collect Fuelwood	How long does it take you to walk from your dwelling to where you usually go to collect the fuelwood (one-way)?	Minutes
Post-Harvest Efforts	When you collect fuelwood, do you take measures to encourage regrowth or post-harvest management?	No=0: Yes=1
Time Collecting Fuelwood Change in Last 5 years	Does your household spend more or less time collecting firewood than you did 5 years ago?	1=More, 2=About the same, 3=Less
Collect Fuelwood from Land Type	Where do you most frequently go to collect the fuelwood?	1=Natural forest/woodland, 2=Plantation/woodlot , 3=Trees on farms (own farm), 4=Trees on farms (not own farm) , 99=Others (Specify)
Collect Fuelwood from Land Ownership	What is the ownership status of the forest/woodlot/farm where you most frequently go do collect fuelwood?	1=Government/state, 2=Community owned , 3=Private, 4=Open access , 99=Other (Specify)

Table 2. Wording of Relevant Questions

This table provides the actual wording of the questions used in this study. The variable descriptions are used throughout the paper, and these questions are how those variables were collected.

Variable	**VIF All**

treesplant	1.039134926
totalland	1.04163877
infoagrofo	1.018119918
woodhardto	1.006753378
timefw	1.028491056
fwlandowns	1.017980659
pharvestac	1.008378867
lulcc	1.015565393

Table 3. VIF Analysis

The VIF analysis provides an indication of the multicollinearity of the variables that are used in the regressions. The above chart shows values around 1, which are accepted as low co-dependence. The variables with VIF result above 1.5 were eliminated, because when they were added to a multivariate regression, the multicollinearity was above the acceptable limit of 30.

	Total Land Owned	% that Plant Trees	Information on Agroforestry	Wood Hard to get	Kilometers to Collect Fuelwood	Collected from Plantation
% that Planted Trees	0.8308 **	1				
Agroforest Info	-0.0325	0.1508	1			
Wood hard to get	-0.4949 *	-0.6057*	0.0357	1		
Km to Collect fw	-0.0396	-0.1178	-0.07623	0.2153	1	
Plantation	0.00815	-0.0158	-0.5943*	-0.2680	0.2533	1
Private	0.1045	0.2121	-0.5061*	-0.3411	-0.02949	0.8514 **

Table 5. Correlation Matrix of Significant Variables

This table shows the correlation values run through Excel's correlation tool to see general trends at the village cluster level (16 village clusters) between separate variables. A value of 0 shows no correlation at all, 1 is a perfect positive correlation and -1 is a perfect negative correlation. There are 10 values of interest with correlation coefficients with moderate or strong correlation (coefficient greater than 0.3).

Variable of Interest	**Mulanje**	**Thyolo**	**Chiradzulu**	**Total**
Total Land Owned	1.202 acres	0.785 acres	1.653 acres	1.212 acres
Information on Agroforestry	21% yes	19.6% yes	30.4% yes	23.7% yes
Land Use Land Cover Change Classification				
Planted Trees	30.3% yes	24.6% yes	23.7% yes	28.2% yes
Distance to Home Forest	52.2 minutes	53.3 minutes	38.7 minutes	48.1 minutes
Wood Hard to Get (perception)	81.6% agree	86.0% agree	82.6% agree	83.4% agree
Time to Collect Fuelwood	45.3 minutes	46.8 minutes	33.8 minutes	42.0 minutes
Post-Harvest Efforts	8.67% yes	8.97% yes	7.35% yes	8.33% yes
Collect Fuelwood from Forests	51%	37.5%	60.8%	49.8%
Collect Fuelwood from Plantations	26.6%	34.9%	13.4%	21.0%
Collect Fuelwood from Own Farm	7.00%	8.97%	16.0%	10.7%

Collect Fuelwood from Not Owned Farm	5.67%	8.63%	7.69%	7.34%
Collect Fuelwood from Government Owned Land	51.0%	37.5%	60.8%	49.8%
Collect Fuelwood from Community Owned Land	26.7%	34.9%	13.3%	21.0%
Collect Fuelwood from Privately Owned Land	7.0%	8.97%	16.0%	10.7%
Collect Fuelwood from Open Access Land	5.67%	8.63%	7.69%	7.33%

Table 6. Descriptive Statistics of Variables of Interest
The descriptive statistics of survey responses in the three major districts and the total dataset

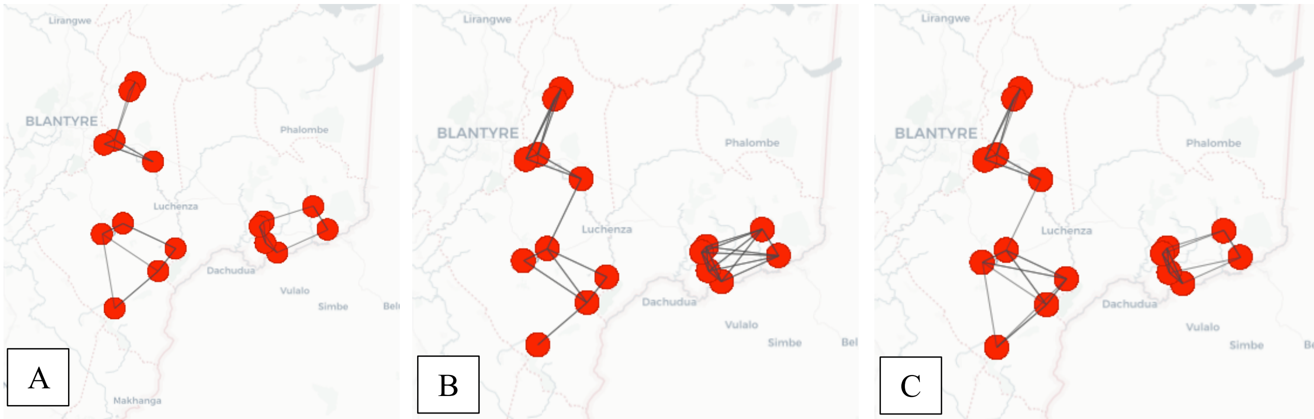


Figure 1: Differences in the Connectivity of Weights
The connectivity of the village clusters as measured by different weights (a) 2 K- Nearest Neighbors Weight (b) 20 km Distance Weight calculated with arc distance (c) Uniform Adaptive Kernel with 1 Diagonal weight and the maximum K-Nearest Neighbors as the band width. The uniform adaptive kernel is used throughout the paper.

Reason	**Percentage of 236 Total 'First Reason' Responses**	**Percentage of 380 Total Reasons**
Fruit	55.9 %	34.7 %
Fuel	25.4 %	31.1 %
Fencing	10.6 %	21.8 %
Biofuel (i.e. ethanol)	3.81 %	3.68 %
Other	2.97 %	5.79 %
Fodder	0.847 %	0.789 %
Ornament	0.423 %	2.10 %

Figure 2. Reasons Trees were Planted
Responses for the question regarding the reason for planting trees. The percentage of 'first reason' is the first response to the question, and the percentage of total reasons includes the second reason (if) cited.

Works Cited

Abbot, J. I. (1996). *Rural Subsistence and Protected Areas : Community Use of the miombo woodlands of Lake Malawi National Park*. (February).

Abbot, J. I. O., & Mace, R. (1999). Managing protected woodlands: Fuelwood collection and law enforcement in Lake Malawi National Park. *Conservation Biology*, *13*(2), 418–421.

Agbemabiese, L., Nkomo, J., & Sokona, Y. (2012). Enabling innovations in energy access: An African perspective. *Energy Policy*, *47*(SUPPL.1), 38–47.

Bailis, R., Drigo, R., Ghilardi, A., & Masera, O. (2015). The carbon footprint of traditional woodfuels. *Nature Climate Change*, *5*(3), 266–272.

Balachandra, P. (2011). Modern energy access to all in rural India: An integrated implementation strategy. *Energy Policy*, *39*(12), 7803–7814.

Bewket, W. (2003). Household Level Tree Planting and its Importance for Environmental Management in the North-Western Highlands of Ethiopia: A Case Study in the Chemoga Watershed, Blue Nile Basin. *Land Degredation and Development*, *14*, 377–388.

Brew-Hammond, A. (2010). Energy access in Africa: Challenges ahead. *Energy Policy*, *38*(5), 2291–2301.

Brouwer, I. D., Hoorweg, J. C., & Van Liere, M. (1997). When Households Run Out of Fuel: Responses of Rural Households to Decreasing Fuelwood Availability, Ntcheu District, Malawi. *World Development*, *25*(2), 255–266.

Brouwer, I. D., Wijnhoven, T. M. A., Burema, J., & Hoorweg, J. C. (1996). Household fuel use and food consumption: Relationship and seasonal effects in Central Malawi. *Ecology of Food and Nutrition*, *35*(3), 179–193.

Fall, L. (2005). Energy Access: Illusion or Reality for the Poor? *Energy & Environment*, *16*(5), 743–761.

Faye, P., & Ribot, J. (2017). Causes for adaptation: Access to forests, markets and representation in Eastern Senegal. *Sustainability (Switzerland)*, *9*(2), 1–20.

Garcia, M., & Moore, C. (2012). *The Rise of Cash Transfer Programs in Sub-Saharan Africa*.

Gujba, H., Thorne, S., Mulugetta, Y., Rai, K., & Sokona, Y. (2012). Financing low carbon energy access in Africa. *Energy Policy*, *47*(SUPPL.1), 71–78.

Hartter, J., & Boston, K. (2007). An integrated approach to modeling resource utilization for rural communities in developing countries. *Journal of Environmental Management*, *85*(1), 78–92.

He, G., Chen, X., Beaer, S., Colunga, M., Mertig, A., An, L., … Liu, J. (2009). Spatial and temporal patterns of fuelwood collection in Wolong Nature Reserve: Implications for panda conservation. *Landscape and Urban Planning*, *92*(1), 1–9.

Heltberg, R., Arndt, T. C., & Sekhar, N. U. (2000). Fuelwood Consumption and Forest Degradation: A Household Model for Domestic Energy Substitution in Rural India. *Land Economics*, *76*(2), 213.

Hyde, W. F., & Seve, J. E. (1993). The economic role of wood products in tropical deforestation: the severe example of Malawi. *Forest Ecology and Management*, *57*(1–4), 283–300.

Iiyama, M., Neufeldt, H., Dobie, P., Njenga, M., Ndegwa, G., & Jamnadass, R. (2014). The potential of agroforestry in the provision of sustainable woodfuel in sub-Saharan Africa. *Current Opinion in Environmental Sustainability*, *6*(1), 138–147.

IPCC. (2014). Climate Change 2014: Synthesis Report. In *Climate Change 2014: Synthesis*.

Jagger, P., & Kittner, N. (2017). Deforestation and biomass fuel dynamics in Uganda. *Biomass and Bioenergy*, *105*, 1–9. https://doi.org/10.1016/j.biombioe.2017.06.005

Jagger, P., & Perez-Heydrich, C. (2016). Land use and household energy dynamics in Malawi. *Environmental Research Letters*, *11*(12).

James Cook, R. (1992). Wheat root health management and environmental concern. *Canadian Journal of Plant Pathology*, *14*(1), 76–85.

Karna, Y. K., Hussin, Y. A., Gilani, H., Bronsveld, M. C., Murthy, M. S. R., Qamer, F. M., … Baniya, C. B. (2015). Integration of WorldView-2 and airborne LiDAR data for tree species level carbon stock mapping in Kayar Khola watershed, Nepal. *International Journal of Applied Earth Observation and Geoinformation*, *38*, 280–291.

Karna, Y. K., Hussin, Y. A., Gilani, H., Bronsveld, M. C., Murthy, M. S. R., Qamer, F. M., … Baniya, C. B. (2015). Integration of WorldView-2 and airborne LiDAR data for tree species level carbon stock mapping in Kayar Khola watershed, Nepal. *International Journal of Applied Earth Observation and Geoinformation*, *38*, 280–291.

Kohlin, G., & Parks, P. J. (2006). Spatial Variability and Disincentives to Harvest: Deforestation and Fuelwood Collection in South Asia. *Land Economics*, *77*(2), 206.

Lund, J. F., Rutt, R. L., & Ribot, J. (2018). Trends in research on forestry decentralization policies. *Current Opinion in Environmental Sustainability*, *32*, 17–22.

Mauambeta, D., D, C., R, M., & S, G. (2010). Status of forests and tree management in Malawi. *Researchgate*, (September 2010).

Miteva, D. A., Kramer, R. A., Brown, Z. S., & Smith, M. D. (2017). Spatial patterns of market participation and resource extraction: Fuelwood collection in Northern Uganda. *American Journal of Agricultural Economics*, *99*(4), 1008–1026.

Pearson, P. J. G., & Stevens, P. (1989). The Fuelwood Crisis and the Environment. *Energy Policy*, *17*(2), 132.

Preston, K., Pypker, T. G., & Orr, B. (2017). Women and fuelwood in Lupeta, Tanzania: Constraints to alternative fuels and fuelwood management strategies. *Journal of Sustainable Forestry*, *36*(6), 555–567.

Pullanikkatil, D., Palamuleni, L., & Ruhiiga, T. (2016). Assessment of land use change in Likangala River catchment, Malawi: A remote sensing and DPSIR approach. *Applied Geography*, *71*, 9–23.

Rahut, D. B., Behera, B., & Ali, A. (2016). Patterns and determinants of household use of fuels for cooking: Empirical evidence from sub-Saharan Africa. *Energy*, *117*, 93–104.

Sokona, Y., Mulugetta, Y., & Gujba, H. (2012). Widening energy access in Africa: Towards energy transition. *Energy Policy*, *47*(SUPPL.1), 3–10.

Specht, T. D., & Rosendahl, B. R. (1989). Architecture of the Lake Malawi Rift, East Africa. *Journal of African Earth Sciences*, *8*(2–4), 355–382.

Srivastava, L., Goswami, A., Diljun, G. M., & Chaudhury, S. (2012). Energy access: Revelations from energy consumption patterns in rural India. *Energy Policy*, *47*(SUPPL.1), 11–20.

Toole, R. (2015). *The Energy Ladder : A Valid Model for Household Fuel Transitions in Sub-Saharan Africa ? A thesis submitted by Rebecca Toole in partial fulfillment of the requirements for the degree of Master of Science in Urban and Environmental Policy and Planning and*. (August).

USAID. Malawi Climate Change Fact Sheet. (2016, September). Retrieved November 28, 2018.

Webb, E. L., & Dhakal, A. (2011). Patterns and drivers of fuelwood collection and tree planting in a Middle Hill watershed of Nepal. *Biomass and Bioenergy*, *35*(1), 121–132.

Webb, E. L., & Dhakal, A. (2011). Patterns and drivers of fuelwood collection and tree planting in a Middle Hill watershed of Nepal. *Biomass and Bioenergy*, *35*(1), 121–132.

Woldeamlak, B. (2005). *Bio-fuel Consumption , Household Level Tree Planting and Its Implications For Environmental Management In The Northwestern Highlands Of Ethiopia*. *388*(April), 377–388.

World Bank. Malawi. (2018). Retrieved November 28, 2018.

Zulu, L. C. (2010). The forbidden fuel: Charcoal, urban woodfuel demand and supply dynamics, community forest management and woodfuel policy in Malawi. *Energy Policy*, *38*(7), 3717–3730.